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BEECLUST used for exploration tasks in Autonomous Underwater Vehicles ⋆

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Abstract: Underwater exploration is still a difficult task these days. In this paper we suggest a swarm of Autonomous Underwater Vehicles (AUVs) for such tasks. These AUVs are controlled by BEECLUST which is a swarm control algorithm inspired by honeybee behaviour. A swarm controlled by BEECLUST shows very reliable aggregation behaviour in a global optimum. In a simulation experiment we show that BEECLUST is very well adaptable for AUV swarms. Furthermore we show that BEECLUST is not only capable of showing aggregation behaviour but also is a valid tool for underwater exploration tasks.

Keywords: Swarm Intelligence, Artificial Life, Emergent Behaviour, Underwater Robotics

1. INTRODUCTION

Oceans are one of the least explored regions on earth. Still relatively little is known about the underwater world. Therefore underwater exploration is a very promising field of research, but the deep sea is a very hostile habitat to human life. This is why underwater robots have already been established for expeditions to the deep sea. Our approach suggests a swarm of Autonomous Underwater Vehicles (AUVs). The advantages of the usage of swarm robots are obvious: single AUVs are mostly large, expensive, require a lot of hardware and internal memory. A swarm of small AUVs however could be operated cost efficiently, has low requirements in hardware and acts in a more reliable way than a single AUV could.

A swarm, in fact, is a loose structure of rather 'simple' individuals which exploit the principles of self-organisation, as described by Camazine et al. (2001). The interaction between individuals in such a swarm happens on a rather basic level. Nevertheless, the behaviour that results from these interactions gets quite complex. The phenomenon of complex group level behaviour, emerging from basic interactions, can be classified with the term 'swarm intelligence' (Millonas, 1994; Bonabeau et al., 1999; Kennedy and Eberhart, 2001). Especially the field of biology offers manifold examples of swarm behaviour from which engineers can get their inspiration for algorithms: staring with rather simple life forms such as slimemolds (Nakagaki, 2001) to social insects such as ants (Deneubourg et al., 2002) and honeybees (Seeley et al., 1991) to more complex animals such as fish (Breder, 1954, 1951) and even mammals (Gueron and Levin, 1993).

In this work we present the results of simulation experiments, which were performed within the CoCoRo Project (CoCoRo, 2013). In recent years, several projects have conducted scientific research on underwater robotics: The FILOSE Project (Kruusmaa et al., 2014) investigates how fish sense the flow around them and react to the changes in the flow pattern. The overall aim of FILOSE is to acquire a deeper understanding of the principles underlying fish locomotion and sensing, in order to develop new technologies for underwater vehicles on the basis of biological evidence. An important component of this project is the investigation of the sensing capabilities of the lateral line organ. In contrast to that the CoCoRo Project will conduct research on a swarm of AUVs which also use collective cognition, artificial immune systems and long-term autonomous principles. The Project Co3-AUVs (Antonelli et al., 2010) wants to develop a swarm of AUVs to seamlessly monitor critical underwater infrastructures and to detect anomalous situations (e.g., missions related to harbour safety and security). The project also wants to study if advanced AUVs are capable of interacting with humans to perform such functions as companion/support platforms during scientific and commercial dives. In contrast to that the CoCoRo Project does not put emphasis on human AUV interaction, instead the project focuses on making the AUVs as autonomous as possible.

1.1 Honeybee aggregation

In this work we performed simulated experiments with a bio-inspired algorithm called BEECLUST, which is inspired by honeybee behaviour. Young honeybees (*Apis melifera*) prefer an ambient temperature of 36 °C. This temperature corresponds to the temperature found within the centre of the brood nest of a beehive, as described by Heran (1952). Groups of young honeybees, when exposed to a 2-dimensional thermal gradient, form an aggregation at 36 °C (Szopek et al., 2009, 2013). The majority of single bees however does not have the ability to position themselves within this optimum temperature spot on their own. They move around almost randomly. This aggregation behaviour emerges from quite simple bee-to-bee interactions: when a bee encounters another bee she

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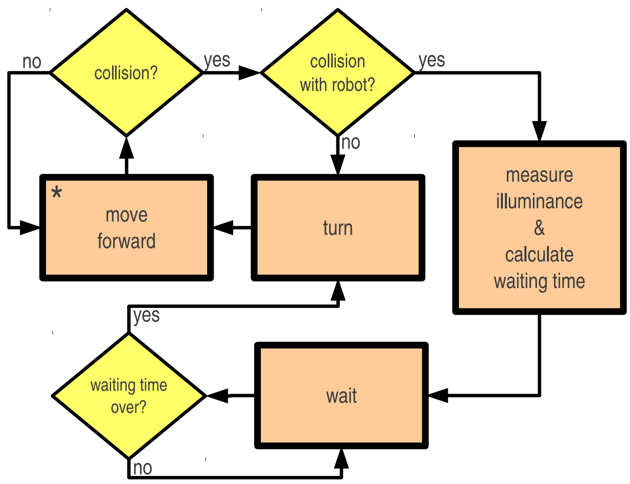

Fig. 1. Finite state machine of the BEECLUST controller. The asterisk indicates the starting state of the algorithm. Please note that the experiments in this work were performed with a depth sensor and therefore we measured the depth instead of the illuminance.

stops and waits. The waiting time correlates with the local encountered temperature. The warmer it is, the longer the bee will wait (Kernbach et al., 2009). But groups of young honeybees do not only find the optimum temperature spot, they are also able to react to changes in this temperature environment. In a 2-dimensional thermal gradient which provides an optimum (36 °C) and a sub-optimum (32 °C) temperature spot the bees first aggregate in the optimum. But when the optimum gets removed from the thermal gradient, which means the sub-optimum becomes the new optimum, the bees start to aggregate in the new 32 °C optimum (Szopek et al., 2010, 2013).

1.2 The BEECLUST algorithm

Using this knowledge of the honeybee aggregation behaviour, Schmickl et al. (2008) developed the honeybee inspired aggregation algorithm called BEECLUST. In contrast to the bees, which measure the local temperature, the robots used by Schmickl et al. (2008) were tested in a 2-dimensional light gradient. Therefore the robots were equipped with a light sensor and measured the local illuminance.

The BEECLUST algorithm follows a few simple rules:

(1) Robots move around randomly;
(2) Whenever a robot meets an obstacle, the robot checks whether the obstacle is another robot or a wall;
(3) If the obstacle is a wall, the robot turns and proceeds with step 1;
(4) If the obstacle is another robot, the robot stops and calculates a waiting time. The brighter it is, the longer the robot waits;
(5) After the waiting time has expired, the robot proceeds with step 1.

A graphical depiction of the finite state-machine of BEECLUST can be seen in figure 1. These very simple rules lead to an aggregation cluster of robots in the brightest spot.

BEECLUST has not only be proven to act very robust (Bodi et al., 2009, 2012, 2011) but also fulfils all needs to be classified as ‘swarm intelligent’ (Schmickl et al., 2008). In Kengyel et al. (2011), robots were equipped with temperature sensors and tested in a real temperature gradient. In Hamann et al. (2012), a more general model of BEECLUST was analysed considering its symmetry breaking abilities. Detailed analyses of BEECLUSTs aggregation abilities were performed by Kernbach et al. (2013).

The hardware requirements needed for performing BEECLUST are very low. Basically, a robot-to-robot detection and one environmental sensor satisfy the needs for showing aggregation behaviour. No internal memory, global information or further knowledge of position or number of robots are required. Due to its simplicity and low requirements, BEECLUST is very easily adaptable for all kinds of swarm robots. Furthermore BEECLUST can be operated with any given environmental sensor and its corresponding environmental stimuli. As it has been shown by Schmickl et al. (2008) BEECLUST is not only a simple aggregation algorithm. A swarm of robots controlled by BEECLUST is able to discriminate between different environmental properties and responds to spontaneous changes of these properties. Furthermore it has been shown that two swarms of robots, each performing a different task in the same area of operation, are able to help each other in their ability to aggregate (Bodi et al., 2009, 2012, 2011). These advantages make BEECLUST a very interesting control algorithm for AUVs.

This work discusses the questions whether or not BEECLUST is adaptable for a swarm of AUVs and if this algorithm can be utilized for underwater exploring tasks.

2. METHODS

2.1 Experimental set up

The following experiments were performed in ‘CoCoRoSim’, a simulation environment which is specially designed for simulations of AUVs (Read et al., 2013). This simulator was completely written in NetLogo (Wilensky, 1999). A screenshot of the experimental arena and its starting conditions can be seen in figure 2. For these experiments we chose the ground level to be the decisive factor for aggregation. We generated an environment with the dimensions of 100·100·42 patches (l·w·h). In this model, a patch is is a cube with an edge length of one AUV diameter (10 cm). This experimental environment is further called arena. The edges of the arena are impenetrable and can be considered as walls. The ground is designed to show a more or less irregular random pattern. As aggregation spots we introduced two depressions in the ground. One depression is located on the front left side of the arena, the other depression is located on the rear right of the arena. This positioning of the depressions provides a maximum distance between the two aggregation spots. The left depression has a depth of 9 patches whereas the right depression has a depth of 7 patches. Therefore the left depression can be considered to be the optimal aggregation spot whereas the right depression can be considered to be the suboptimal aggregation spot. Within the arena

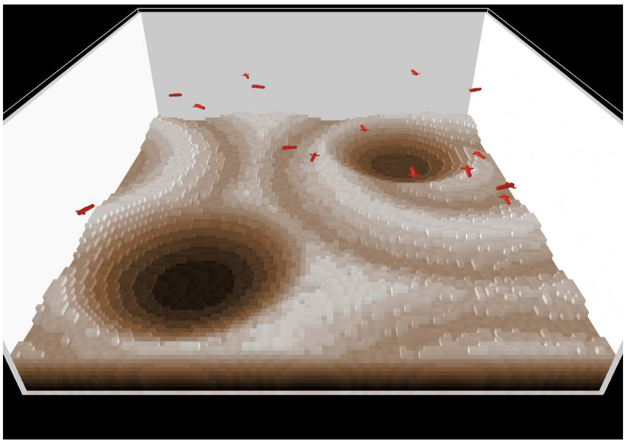

Fig. 2. Screenshot of the experimental arena and its starting conditions. The red objects are AUVs. The two depressions in the ground represent the aggregation spots whereby the left depression can be considered to be the optimal spot for aggregation. At the beginning of each experimental run the AUVs were spawned at random positions.

the AUVs moved along the ground terrain using only buoyancy for changing their altitude. At the beginning of each experimental run the AUVs were spawned at random positions.

We tested different group sizes of AUVs with different waiting times. The tested group sizes were 10, 20, 30, 40 and 50 AUVs. The initial value of the maximum waiting time was 480 seconds. For investigating an optimal waiting time for the given environment we observed experiments using different waiting times. The waiting times were varied by a waiting time multiplicator. The used values for this multiplicator can be found in table 1. Each combination of group size and waiting time was tested 50 times for a duration of 250 simulated minutes.

2.2 The AUVs

The experiments were performed with simulated Autonomous Underwater Vehicles (AUVs). These AUVs are simplified models of real life Lily AUVs, which were developed within the CoCoRo Project (Read et al., 2013; CoCoRo, 2013). In our simulation, an AUV is a sphere with a diameter of 10 cm. The AUVs are equipped with two thrusters, one on the left, the other one on the right side. So the AUVs have the ability to move forward and backwards and turn on their z-axis, meaning the AUVs are able to yaw. No pitch or roll were used in this simulation. The maximum speed of the AUVs is 20 cm/sec. Please note that in our experiment no backwards movement was used. The AUVs also have the ability to change their buoyancy, which enables upwards and downwards movement.

Each AUV is equipped with 6 simulated distance sensors: 4 sensors on each side (front, back, left, right), one sensor upward and one sensor downward. Each sensor field s is modelled as a cone

$$s = \frac{1}{3}\pi r^2 h, \tag{1}$$

where the radius r is 242.97cm and the height h is 150cm. This results in an aperture of the sensor cone of $\phi = 90°$ These sensors are used for collision avoidance and AUV detection. Furthermore the AUVs are equipped with a pressure sensor for receiving information about their current diving depth.

2.3 Modelling the waiting time of the AUVs

To achieve an aggregation behaviour in the depressions we used the pressure sensors of the AUVs as environmental sensor. This means that the waiting time of the AUV is correlated to its current depth. The deeper the AUV is, the longer it will wait.

The waiting time of the AUVs were calculated as follows:

$$w = \frac{w_{max}\mu}{1 + exp^{-(e+o)\sigma}}, \tag{2}$$

where w refers to the waiting time, w_{max} is modelled as the maximum waiting time, μ represents a waiting time multiplicatior, e is the the AUV's current sensor value, o represents the vertical offset of the waiting time function and σ refers to the steepness of this function. The values used in equation 2 can be seen in table 1.

Table 1. Values used in equation 2

variable	values	dimensions
w_{max}	480	sec
μ	1, 3, 5, 7, 10	dmnl
o	150	dmnl
σ	0.1	dmnl

2.4 Physics

We implemented three basic 'kinetic calculations' of underwater physics: movement in x- and y-direction, buoyancy (including weight force) and drag. The movement in x- and y-direction is realised via the calculation of two different values: the distance the AUV covers and the heading of the AUV. To decrease the failure of the simulation the movement is separated into a pre-movement-turn, forward-movement and a post-movement-turn. The calculation of the drag F_D is based on the Morison equation (Morison et al., 1950) and modelled as:

$$F_D = \frac{1}{2}\rho v^2 C_D A \tag{3}$$

where ρ is the density of the water ($1000kg/m^3$), v is the velocity, C_D is the drag-coefficient (0.45) and A is the cross section area (AUV length · AUV height). The movement in z-direction is controlled via the buoyancy with an input-voltage between 0V and 5V. An input-voltage of 2.5V means, that the AUV has the exact water density and thus will stay at the current depth.

In this model, no currents have been implemented. The aim of this work is not to introduce a realistic simulator for underwater applications, but to investigate if BEECLUST is in principle a feasible control algorithm for a swarm of AUVs executing exploration tasks.

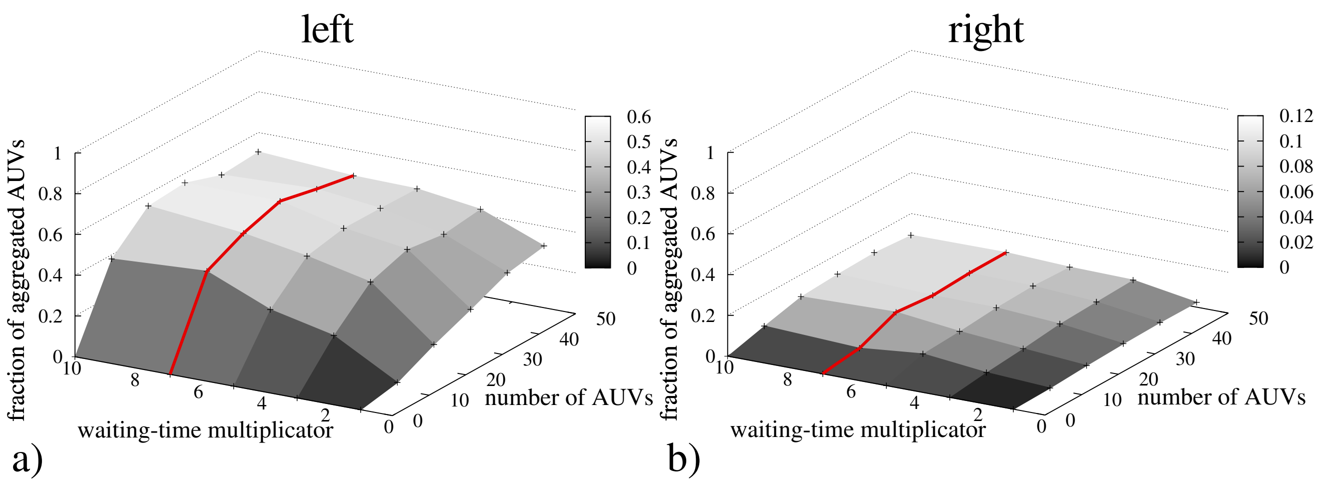

Fig. 3. Fraction of aggregated AUVs. The left target represents the optimal spot for aggregation. In all experimental runs the AUVs aggregated in the optimal aggregation spot. n = 50 repetitions per experiment. The red line indicates an example result which is depicted in figure 4.

3. RESULTS

For getting an idea of the quality of the aggregations we analysed the fraction of aggregated AUVs in the two opposing target zones. The target zones were defined as the circular areas above the depressions. Each target zone was analysed separately and due to their spatial positions within the experimental arena the optimal aggregation zone is further called ‘left target’, whereas the suboptimal aggregation zone is further called ‘right target’. We chose this kind of evaluation because in swarm robotics it is important that the swarm works together. So the absolute number of aggregated AUVs is not as important as the fraction of aggregated AUVs.

At first we take a closer look at how the tested group sizes affect the aggregation. Figure 3a shows that a clear swarm effect is observable. The mean values of 50 repetitions are shown. In groups of one to 30 individuals, the fraction of aggregated AUVs increases with rising number of individuals in the swarm. But the aggregation quality decreases in groups which have more than 30 individuals. One exception is the experimental run using a waiting time multiplicator of 1. In this special case no decreases in the aggregation quality are observable. The highest fraction of aggregated AUVs (0.553) can be observed at a group size of 30 AUVs using a waiting time multiplicator of 10.

When varying the waiting time we see that the fraction of aggregated AUVs correlates with the waiting time. The longer the waiting time, the higher the fraction of aggregated AUVs. When comparing figure 3a to figure 3b we see, that in all possible combinations of group size and waiting time, the majority AUV swarm has aggregated in the left depression.

Figure 4 shows an example experiment using a waiting time multiplicator of 7. Shown are the mean values of 50 repetitions and their corresponding standard deviations. (In Figure 3 this example run is marked as red line.) In this example, we see that in groups of one to 30 individuals the fraction of aggregated AUVs correlates to the total number of AUVs in the swarm: the more individuals the better the aggregation quality. Beyond 30 individuals the aggregation quality decreases. This means that we found an optimal group size of 30 individuals for the given experimental setup. In this case a fraction of 0.549 AUVs (stdev = 0.122) aggregated at the left target. Figure 4 also clearly shows, that in all cases the swarm aggregated in the left target.

4. DISCUSSION

Figure 3a and figure 4a show that a clear swarm effect emerges. This means that the aggregation quality gets better with increasing number of individuals. This swarm effect is valid for groups from one to 30 AUVs. Beyond this group size the aggregation quality decreases. This can be explained by the fact that the aggregation spot shows an indication of saturation. In larger AUV groups also jamming effects occur, which also lead to a lower aggregation quality. One exception is the experimental run using a waiting time multiplicator of 1. In this case the individual waiting time is too short to form a long lasting aggregation. The shorter the waiting time is, the faster the AUVs leave the aggregation. This leads to a lower probability of an AUV meeting another AUV in the cluster. But in this case the swarm effect is still indicated: the more AUVs are used in the experiment, the higher the aggregation quality .

In all experimental runs the AUV swarm has aggregated in the left target (see figures 3a and 3b). Since the starting positions of the AUVs were randomised, a bias of the results, caused by different starting conditions, can be neglected. As it has been shown if figure 1, agents controlled by BEECLUST do not move uphill towards a gradient, but move randomly. When AUVs encounter each other in the optimal aggregation spot they form an aggregation seed. Because of the longer waiting time in the optimum, the probability for other AUVs to encounter this aggregation is increased and the size of the aggregation rises. This feedback loop leads to a stable aggregation in the optimum and prevents larger aggregations in the suboptimum.

As already mentioned above, the left target has a larger diameter and is deeper then the right target. Therefore the

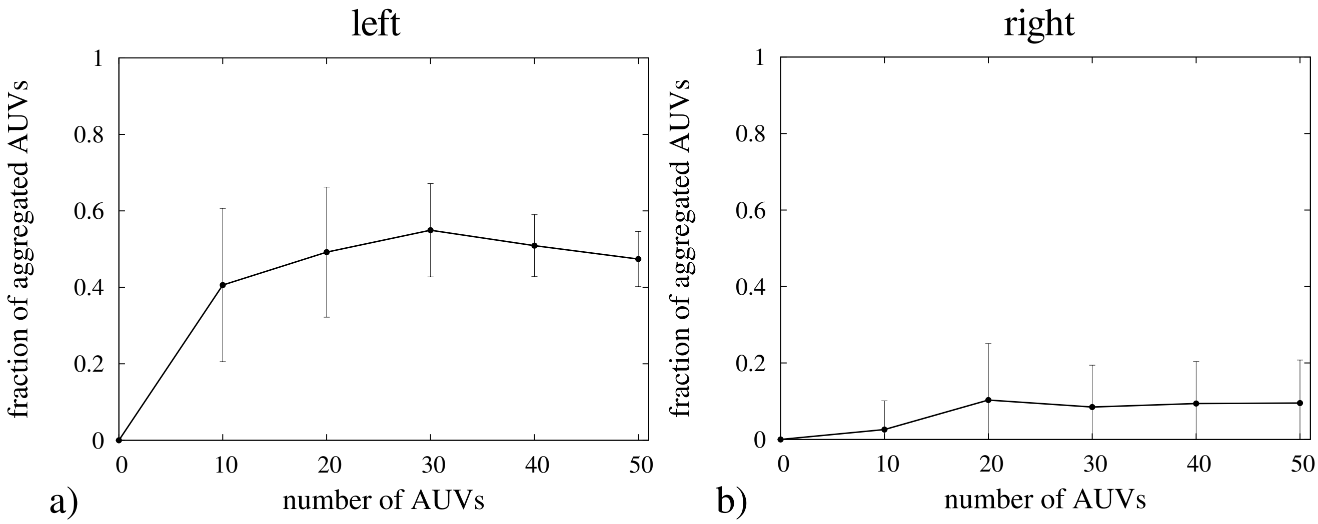

Fig. 4. Fraction and standard deviation of aggregated AUVs. The left target represents the optimal spot for aggregation. n = 50 repetitions per experiment.

left target can be considered to be the optimal aggregation spot for the AUVs. This result means that BEECLUST is very well adaptable for swarms of AUVs.

Another advantage of BEECLUST is that this algorithm does not need communication in terms of exchange of information. The only essential interaction between AUVs is robot-to-robot detection. Since communication under water is a very complex task, BEECLUST is a very reliable tool for underwater tasks.

The fact that the AUVs 'chose' the optimal aggregation spot does not only show that BEECLUST is suitable for aggregation tasks but proves that AUVs using BEECLUST can also discriminate between different environmental qualities. In our experiments we used the pressure sensor of the AUVs to evaluate the depth of the ground. This way the swarm of AUVs was able to locate the deepest spot of the experimental arena. However BEECLUST works with any given environmental sensor which makes BEECLUST applicable for manifold exploring tasks. Such tasks could be the detection of blackboxes of drowned airplanes or toxic waste dumps containing leaking barrels. Whilst a single AUV could get stuck in a local optimum a swarm of AUVs controlled by BEECLUST would be able to find the global optimum even if the gradient is irregular and complex. Furthermore BEECLUST acts quite robust regarding the group size of the AUV swarm. The loss of single individuals does not greatly influence the ability to form aggregations (Bodi et al., 2012, 2011). Therefore we consider BEECLUST to be a very potent and reliable algorithm for all kinds of swarm robotic applications.

5. CONCLUSION AND FUTURE WORK

Due to its simplicity, low requirements and no need for global information BEECLUST is very easily adaptable for all kinds of swarm robots and countless environmental conditions. This makes BEECLUST an interesting algorithm for AUV swarms. BEECLUST is not only a robust algorithm for aggregation behaviour. Due to its ability to discriminate different environmental conditions BEECLUST can be considered to be a strong and reliable tool for exploration tasks.

In future, this model will be further investigated in terms of aggregation speed. More realistic physics of water currents and AUV movement will be implemented. Furthermore, BEECLUST will be implemented into real Lily AUVs.

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